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Near-Optimal Signal Detector Based on Structured Compressive Sensing for Massive SM-MIMO

Zhen Gao, Linglong Dai, Chenhao Qi, Chau Yuen, and Zhaocheng Wang

***Abstract*—Massive spatial-modulation multiple-input multiple-output (SM-MIMO) with high spectrum efficiency and energy efficiency has recently been proposed for future green communications. However, in massive SM-MIMO, the optimal maximum-likelihood detector has the high complexity, whereas state-of-the-art low-complexity detectors for small-scale SM-MIMO suffer from an obvious performance loss. In this paper, by exploiting the structured sparsity of multiple SM signals, we propose a low-complexity signal detector based on structured compressive sensing (SCS) to improve the signal detection performance. Specifically, we first propose the grouped transmission scheme at the transmitter, where multiple SM signals in several continuous time slots are grouped to carry the common spatial constellation symbol to introduce the desired structured sparsity. Accordingly, a structured subspace pursuit (SSP) algorithm is proposed at the receiver to jointly detect multiple SM signals by leveraging the structured sparsity. In addition, we also propose the SM signal interleaving to permute SM signals in the same transmission group, whereby the channel diversity can be exploited to further improve signal detection performance. Theoretical analysis quantifies the gain from SM signal interleaving, and simulation results verify the near-optimal performance of the proposed scheme.**

***Index Terms*—Massive multiple-input multiple-output (MIMO), signal detection, signal interleaving, spatial modulation (SM), structured compressive sensing (SCS).**

I. Introduction

Spatial-modulation multiple-input multiple-output (SM-MIMO) exploits the pattern of one or several simultaneously active antennas out of all available transmit antennas to transmit extra information [1], [2]. Compared with small-scale SM-MIMO, which only introduces the limited gain in spectrum efficiency, massive SM-MIMO has recently proposed by integrating SM-MIMO with massive MIMO working at 3–6 GHz to achieve higher spectrum efficiency [1]. In massive SM-MIMO systems, the base station (BS) uses a large number of low-cost antennas for higher spectrum efficiency but only one or several power-hungry transmit radio frequency (RF) chains to save power, whereas the user can compactly employ the multiple receive diversity antennas with low correlation [2]. Since the power consumption and hardware cost are largely dependent on the number of simultaneously active transmit RF chains (particularly the power amplifier), massive SM-MIMO outperforms the traditional MIMO schemes in higher spectrum efficiency, reduced power consumption, lower hardware cost, etc. In practice, SM can be adopted in conventional massive MIMO systems as an energy-efficient transmission mode. Meanwhile, massive SM-MIMO can be also considered as an independent scheme to reduce both power consumption and hardware cost.

For massive SM-MIMO, due to the small number of receive antennas at the user and massive antennas at the BS, the signal detection is a challenging large-scale underdetermined problem. When the number of transmit antennas becomes large, the optimal maximum likelihood (ML) signal detector suffers from the prohibitively high complexity [3]. Low-complexity signal vector (SV)-based detector has been proposed for SM-MIMO [3], but it is confined to SM-MIMO with a single transmit RF chain. In [4]–[6], the SM is generalized, where more than one active antennas are used to transmit independent signal constellation symbols for spatial multiplexing. Linear minimum mean square error (LMMSE)-based signal detector [1] and sphere decoding (SD)-based detector [7] can be used for SM-MIMO systems with multiple transmit RF chains. However, they are only suitable for well or overdetermined SM-MIMO with $N_r \geq N_t$ and suffer from a significant performance loss in underdetermined SM-MIMO systems with $N_r < N_t$, where N_t and N_r are the numbers of transmit and receive antennas, respectively. Due to a limited number of RF chains, SM signals have the inherent sparsity, which can be considered by exploiting the compressive sensing (CS) theory [8] for improved signal detection performance. By far, CS has been widely used in wireless communications [9]–[12], and the CS-based signal detectors have been proposed for underdetermined small-scale SM-MIMO [11], [12]. However, their bit-error-rate (BER) performance still has a significant gap compared with that of the optimal ML detector, particularly in massive SM-MIMO with large N_t, N_r, and $N_r \ll N_t$.

This paper proposes a near-optimal structured compressive sensing (SCS)-based signal detector with low complexity for massive SM-MIMO. Specifically, we first propose the grouped transmission scheme at the BS, where multiple successive SM signals are grouped to carry the common spatial constellation symbol to introduce structured sparsity. Accordingly, we propose a structured subspace pursuit (SSP) algorithm at the user to detect multiple SM signals, whereby their structured sparsity is leveraged for improved signal detection performance. Moreover, the SM signal interleaving is proposed to permute SM signals in the same transmission group, so that the channel diversity can be exploited. Theoretical analysis and simulation results verify that the proposed SCS-based signal detector outperforms existing CS-based signal detector.

Notation: Boldface lowercase and uppercase symbols represent column vectors and matrices, respectively. $\lfloor \cdot \rfloor$ denotes the integer floor operator. The transpose, conjugate transpose, and Moore–Penrose matrix inversion operations are denoted by $(\cdot)^T$, $(\cdot)^*$, and $(\cdot)^\dagger$, respectively. The l_p-norm operation is given by $\|\cdot\|_p$, and $|\cdot|$ denotes the

Manuscript received April 8, 2015; revised October 17, 2015 and January 26, 2016; accepted March 31, 2016. Date of publication April 21, 2016; date of current version February 10, 2017. This work was supported in part by the National Natural Science Foundation of China under Grant 61271266 and Grant 61302097, by the International Science and Technology Cooperation Program of China under Grant 2015DFG12760, by the Singapore A∗STAR Project under Grant 142 02 00043, and by the Beijing Natural Science Foundation under Grant 4142027. The review of this paper was coordinated by Dr. Y. Ma.

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Digital Object Identifier 10.1109/TVT.2016.2557625

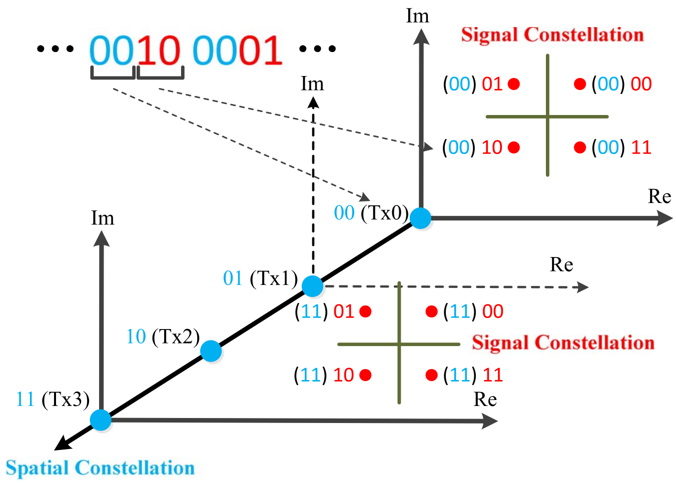

Fig. 1. Spatial constellation symbol and the signal constellation symbol in SM-MIMO systems, where $N_t = 4$, $N_a = 1$, and QPSK are considered an example.

cardinality of a set. $E\{\cdot\}$, $\text{var}\{\cdot\}$, $\text{Re}\{\cdot\}$, and $\text{Im}\{\cdot\}$ are operators to take the expectation, variance, the real part, and the imaginary part of a random variable. $\text{Tr}\{\cdot\}$ is the trace operation for a matrix. If a set has n elements, the number of k-combinations is denoted by the binomial coefficient $\binom{n}{k}$. The index set of nonzero entries of the vector $\mathbf{x}$ is called the support set of $\mathbf{x}$, which is denoted by $\text{supp}\{\mathbf{x}\}$, $\mathbf{x}_i$ denotes the ith entry of the vector $\mathbf{x}$, and $\mathbf{H}_i$ denotes the ith column vector of the matrix $\mathbf{H}$. $\mathbf{x}_\Gamma$ denotes the entries of $\mathbf{x}$ defined in the set Γ, whereas $\mathbf{H}_\Gamma$ denotes a submatrix of $\mathbf{H}$ with indexes of columns defined by the set Γ.

II. System Model

In SM-MIMO systems, the transmitter has N_t transmit antennas but $N_a < N_t$ transmit RF chains, and the receiver has N_r receive antennas. Each SM signal consists of two symbols (see Fig. 1): the spatial constellation symbol obtained by mapping $\lfloor \log_2 \binom{N_t}{N_a} \rfloor$ bits to a pattern of N_a active antennas out of N_t transmit antennas and N_a independent signal constellation symbols coming from the M-ary signal constellation set (e.g., quadrature amplitude modulation). Hence, each SM signal carries the information of $N_a \log_2 M + \lfloor \log_2 \binom{N_t}{N_a} \rfloor$ bits.

At the receiver, the received signal $\mathbf{y} \in \mathbb{C}^{N_r \times 1}$ can be expressed as $\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{w}$, where $\mathbf{x} \in \mathbb{C}^{N_t \times 1}$ is the SM signal transmitted by the transmitter; $\mathbf{w} \in \mathbb{C}^{N_r \times 1}$ is the additive white Gaussian noise (AWGN) vector with independent and identically distributed (i.i.d.) entries following the circular symmetric complex Gaussian distribution $\mathcal{CN}(0, \sigma_w^2)$; $\mathbf{H} = \mathbf{R}_r^{1/2}\tilde{\mathbf{H}}\mathbf{R}_t^{1/2} \in \mathbb{C}^{N_r \times N_t}$ is the correlated flat Rayleigh-fading MIMO channel, with entries of $\tilde{\mathbf{H}}$ being subjected to the i.i.d. distribution $\mathcal{CN}(0,1)$; and $\mathbf{R}_r$ and $\mathbf{R}_t$ are the receiver and transmitter correlation matrices, respectively [13]. The correlation matrix $\mathbf{R}$ is given by $r_{ij} = r^{|i-j|}$, where r_{ij} is the ith row and the jth column element of $\mathbf{R}$, and r is the correlation coefficient of neighboring antennas.

It should be pointed out that $\mathbf{H}$ should be known by the receiver and can be acquired by channel estimation [13]. To achieve both high spectrum efficiency and energy efficiency, massive SM-MIMO, which employs massive low-cost antennas but few power-hungry transmit RF chains at the BS to serve the user with comparatively small number of receive antennas, has recently been proposed [1]. However, its signal detection is a challenging large-scale underdetermined problem since N_t, N_r can be large and $N_r \ll N_t$, e.g., $N_t = 64$ and $N_r = 16$ are considered [1].

For $\mathbf{x}$, the spatial constellation symbol of $\lfloor \log_2 \binom{N_t}{N_a} \rfloor$ bits is mapped into the spatial constellation set $\mathbb{A}$, where the pattern of N_a active antennas selected from N_t transmit antennas is regarded as the spatial constellation symbol. Hence, there are $|\mathbb{A}| = 2^{\lfloor \log_2 \binom{N_t}{N_a} \rfloor}$ kinds of patterns of active antennas, i.e., $\text{supp}\{\mathbf{x}\} \in \mathbb{A}$. Meanwhile, the signal constellation symbol of the ith active antenna, which is denoted by $x^{(i)}$ for $1 \le i \le N_a$, is mapped into the M-ary signal constellation set $\mathbb{B}$. Therefore, the signal detection in SM-MIMO can be formulated as the $M^{N_a} 2^{\lfloor \log_2 \binom{N_t}{N_a} \rfloor}$-hypothesis detection problem. Clearly, the optimal signal detector to this problem is the ML signal detector, which can be expressed as [1]

$$\hat{\mathbf{x}}_{\text{ML}} = \arg \min_{\text{supp}(\mathbf{x}) \in \mathbb{A}, x^{(i)} \in \mathbb{B}, 1 \le i \le N_a} \|\mathbf{y} - \mathbf{H}\mathbf{x}\|_2. \tag{1}$$

However, the computational complexity of the optimal ML signal detector is $\mathcal{O}(M^{N_a} 2^{\lfloor \log_2 \binom{N_t}{N_a} \rfloor})$, which can be unrealistic when N_t, N_a, and/or M become large.

To reduce the complexity, the SV-based signal detector has been proposed [3], but it only considers the case of $N_a = 1$. The LMMSE-based signal detector with the complexity of $\mathcal{O}(2N_r N_t^2 + N_t^3)$ [1] and the SD-based signal detector with the complexity of $\mathcal{O}(\max\{N_t^3, N_r N_t^2, N_r^2 N_t\})$ [7] have been proposed for well or overdetermined SM-MIMO with $N_r \ge N_t$. However, for underdetermined SM-MIMO systems with $N_r < N_t$, these detectors suffer from a significant performance loss [12]. Since only N_a transmit antennas are active in each time slot for power saving and low hardware cost, there are only $N_a < N_t$ nonzero entries in $\mathbf{x}$; thus, the SM signal has the inherent sparsity. By exploiting such sparsity, the CS-based signal detectors have been proposed for SM [10]–[12]. In [10], a spatial modulation matching pursuit (SMMP) algorithm is proposed to detect multiuser SM signals in the uplink massive SM-MIMO systems. In [11] and [12], the CS-based signal detectors are proposed for underdetermined single-user SM-MIMO systems with $N_r < N_t$ in the downlink. The normalized compressive sensing (NCS) detector (with the complexity of $\mathcal{O}(2N_r N_a^2 + N_a^3)$) in [11] first normalizes the MIMO channels and then uses orthogonal-matching-pursuit algorithm to detect signals. In [12], a basis pursuit denoising (BPDN) algorithm (with the complexity of $\mathcal{O}(N_t^3)$) from the classical basis pursuit algorithm is developed to detect SM signals. However, both NCS and BPDN detectors are based on the framework of CS theory, and such CS-based signal detectors still suffer from a significant performance gap compared with the optimal ML detector when N_t/N_r becomes large, particularly in massive SM-MIMO systems with $N_r \ll N_t$ [12].

III. Proposed Structured Compressive Sensing-Based Signal Detector

In this section, an SCS-based signal detector is proposed for downlink single-user massive SM-MIMO as shown in Fig. 2.

A. Grouped Transmission and Interleaving at the Transmitter

We assume that signal constellation symbols in the proposed scheme are mutually independent. Moreover, for the proposed grouped transmission scheme, every G consecutive SM signals are considered as a group, and SM signals in the same transmission group share the same spatial constellation symbol, i.e.,

$$\text{supp}\left(\mathbf{x}^{(1)}\right) = \text{supp}\left(\mathbf{x}^{(2)}\right) = \cdots = \text{supp}\left(\mathbf{x}^{(G)}\right) \tag{2}$$

where $\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \ldots, \mathbf{x}^{(G)}$ are SM signals in G consecutive time slots. Due to the conveyed common spatial constellation symbol, $\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \ldots, \mathbf{x}^{(G)}$ in the same transmission group share the same support set and thus have the structured sparsity. It is clear that to introduce such structured sparsity, the effective information bits carried by spatial constellation symbols will be reduced. However, as will be demonstrated in our simulations, such structured sparsity

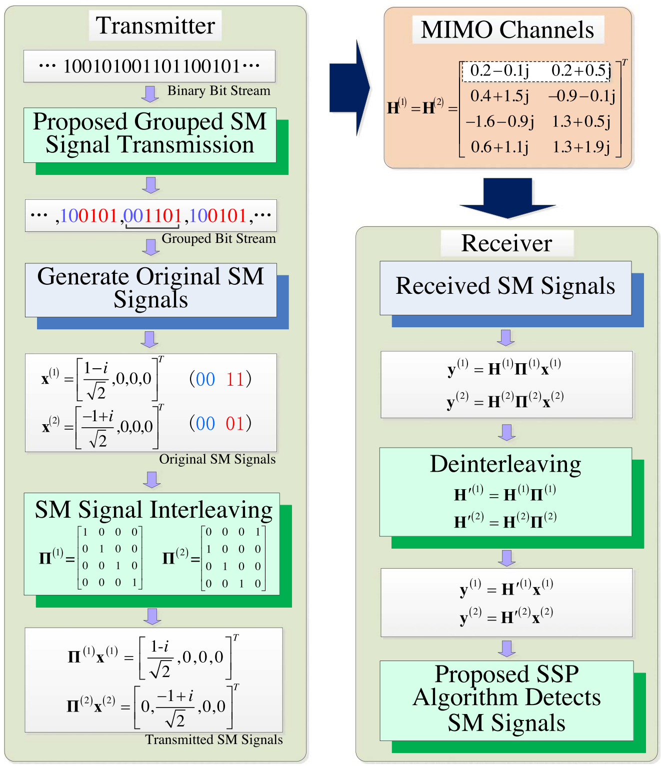

Fig. 2. Proposed SCS-based signal detector, where $N_t = 4$, $N_r = 2$, $N_a = 1$, $G = 2$, and QPSK are considered. Note that the white dot block in MIMO channels denotes the deep channel fading.

allows more reliable signal detection performance and eventually could even improve the BER performance of the whole system without the reduction of the total bit per channel use (bpcu).

On the other hand, due to the temporal channel correlation, channels in several consecutive time slots can be considered to be quasi-static, i.e., $\mathbf{H}^{(1)} = \mathbf{H}^{(2)} = \cdots = \mathbf{H}^{(G)}$, where $\mathbf{H}^{(t)}$ for $1 \le t \le G$ is the channel associated with the tth SM signal in the group. This implies that if channels used for SM fall into the deep fading, such deep fading usually remains unchanged during G time slots, and the corresponding signal detection performance will be poor. To solve this issue, we further propose the SM signal interleaving at the transmitter. Specifically, after the original SM signals $\mathbf{x}^{(t)}$'s are generated, the actually transmitted signals are given by $\mathbf{\Pi}^{(t)}\mathbf{x}^{(t)}$'s, where each column and row of $\mathbf{\Pi}^{(t)} \in \mathbb{C}^{N_t \times N_t}$ only has one nonzero element with the value of one, and $\mathbf{\Pi}^{(t)}$ can permutate the entries in $\mathbf{x}^{(t)}$. We consider that $\mathbf{\Pi}^{(t)}$'s for $1 \le t \le G$ are different in different time slots, and they are predefined and known by both the transmitter and receiver. In this way, the active antennas vary in different time slots from the same transmission group, although $\mathbf{x}^{(t)}$'s share the common spatial constellation symbol. Hence, the channel diversity can be appropriately exploited to improve the signal detection at the receiver. In Section IV-B, such diversity gain will be further discussed.

B. SCS-Based Signal Detector at the Receiver

At the receiver, the received signal in the tth time slot is

$$\mathbf{y}^{(t)} = \mathbf{H}^{(t)}\mathbf{\Pi}^{(t)}\mathbf{x}^{(t)} + \mathbf{w}^{(t)} = \mathbf{H}'^{(t)}\mathbf{x}^{(t)} + \mathbf{w}^{(t)} \qquad (3)$$

where $\mathbf{H}'^{(t)} = \mathbf{H}^{(t)}\mathbf{\Pi}^{(t)}$ is the deinterleaving processing.

From (3), we observe that $\mathbf{x}^{(t)}$'s share the structured sparsity, but they have different nonzero values. According to SCS theory, the structured sparsity of $\mathbf{x}^{(t)}$'s can be exploited to improve the signal detection performance compared with the conventional CS-based signal detectors [8]. Under the framework of SCS theory, the solution to (3) can be achieved by solving the following optimization problem:

$$\min_{\mathrm{supp}(\mathbf{x}^{(t)}) \in \mathbb{A}} \left(\sum_{t=1}^{G} \left\| \mathbf{x}^{(t)} \right\|_p^q \right)^{\frac{1}{q}}$$
$$\text{s.t. } \mathbf{y}^{(t)} = \mathbf{H}'^{(t)}\mathbf{x}^{(t)}, \mathrm{supp}(\mathbf{x}^{(t)}) = \mathrm{supp}(\mathbf{x}^{(1)}) \quad \forall t. \qquad (4)$$

In this paper, based on the classical subspace pursuit (SP) algorithm [8], we propose an SSP algorithm by utilizing the structured sparsity to solve the optimization problem (4) in a greedy way, where $p = 0$ and $q = 2$ are advocated [8].

The proposed SSP algorithm is described in **Algorithm 1**. Specifically, *Lines 1∼3* perform the initialization. In the kth iteration, *Line 5* performs the correlation between the MIMO channels and the residual in the previous iteration; *Line 6* obtains the potential true indexes according to *Line 5*; *Line 7* merges the estimated indexes obtained in *Lines 8∼9* in the previous iteration and the estimated indexes in *Line 6* in the current iteration; after the least squares in *Line 8*, *Line 9* removes wrong indexes and selects N_a most likely indexes; *Line 10* estimates SM signal according to Ω^k; and *Line 11* acquires the residue. The iteration stops when $k > N_a$. Compared with the classical SP algorithm that only reconstructs one sparse signal from one received signal, the proposed SSP algorithm can jointly recover multiple sparse signals with the structured sparsity but having different measurement matrices, where the structured sparsity of multiple sparse signals can be leveraged for improved signal detection performance. Therefore, the classical SP algorithm can be regarded as a special case of the proposed SSP algorithm when $G = 1$, and more details will be discussed in Section IV-A. Another difference should be pointed out that in the steps of *Lines 6* and *9* in **Algorithm 1**, the selected support set should belong to the predefined spatial constellation set $\mathbb{A}$ for enhanced signal detection performance. However, the classical SP algorithm and existing CS-based signal detectors do not exploit such *priori* information of the expected support set [11], [12]. By using the proposed SSP algorithm, we can acquire the estimation of the spatial constellation symbol according to $\mathrm{supp}(\hat{\mathbf{x}}^{(t)})$'s and the rough estimation of signal constellation symbols. By searching for the minimum Euclidean distance between the rough estimation of signal constellation symbols and legitimate constellation symbols, we can finally estimate signal constellation symbols.

Algorithm 1 Proposed SSP Algorithm.

Input: Received signal $\mathbf{y}^{(t)}$, the channel matrix $\mathbf{H}'^{(t)}$, and the number of active antennas N_a, where $1 \le t \le G$.
Output: Estimated SM signal $\hat{\mathbf{x}}^{(t)}$ for $1 \le t \le G$.
1: $\Omega^0 = \emptyset$;
2: $\mathbf{r}^{(t)} = \mathbf{y}^{(t)} \quad \forall t$;
3: $k = 1$;
4: **while** $k \le N_a$ **do**
5: $\mathbf{a}^{(t)} = (\mathbf{H}'^{(t)})^* \mathbf{r}^{(t)} \quad \forall t$;
6: $\Gamma = \arg\max_{\tilde{\Gamma}} \{\sum_{t=1}^{G} \|\mathbf{a}_{\tilde{\Gamma}}^{(t)}\|_2^2, \tilde{\Gamma} \in \mathbb{A}, |\tilde{\Gamma}| = \min\{2N_a, N_r\}$ if $k = 1$ or $|\tilde{\Gamma}| = \min\{N_a, N_r - N_a\}$ if $k > 1\}$;
7: $\Xi = \Omega^{k-1} \cup \Gamma$;
8: $\mathbf{b}_{\Xi}^{(t)} = (\mathbf{H}'^{(t)}_{\Xi})^{\dagger} \mathbf{y}^{(t)} \quad \forall t$;
9: $\Omega^k = \arg\max_{\tilde{\Omega}} \{\sum_{t=1}^{G} \|\mathbf{b}_{\tilde{\Omega}}^{(t)}\|_2^2, \tilde{\Omega} \in \mathbb{A}$ and $|\tilde{\Omega}| = N_a\}$;
10: $\mathbf{c}_{\Omega^k}^{(t)} = (\mathbf{H}'^{(t)}_{\Omega^k})^{\dagger} \mathbf{y}^{(t)} \quad \forall t$;
11: $\mathbf{r}^{(t)} = \mathbf{y}^{(t)} - \mathbf{H}'^{(t)}\mathbf{c}^{(t)} \quad \forall t$;
12: $k = k + 1$;
13: **end while**
14: $\hat{\mathbf{x}}^{(t)} = \mathbf{c}^{(t)} \quad \forall t$;

IV. Performance Analysis

In this section, we will provide the performance analysis.

A. Comparison of SCS-Based and CS-Based Signal Detectors

Typically, existing CS-based signal detectors utilize one received signal vector to recover one sparse SM signal vector, which is a typical single measurement vector (SMV) problem, i.e., $\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{w}$. If multiple sparse signals share the common support set and identical measurement matrix, i.e., $[\mathbf{y}^{(1)}, \mathbf{y}^{(2)}, \ldots, \mathbf{y}^{(G)}] = \mathbf{H}[\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \ldots, \mathbf{x}^{(G)}] + \mathbf{w}$, the reconstruction of $\mathbf{x}^{(t)}$'s from $\mathbf{y}^{(t)}$'s for $1 \leq t \leq G$ can be considered as the multiple-measurement-vector (MMV) problem in SCS theory [8]. The SCS theory has proven that with the same size of the measurement vector, the recovery performance of SCS algorithms is superior to that of conventional CS algorithms [8]. This implies that with the same number of receive antennas N_r, the proposed SCS-based signal detector can outperform conventional CS-based signal detectors.

Compared with the conventional MMV problem, our formulated problem (4) is to solve multiple sparse signals with the common support set but having different measurement matrices. Hence, both conventional SMV problem and MMV problem can be considered the special cases of our problem. If $\mathbf{\Pi}^{(t)}$'s are identical, (4) becomes the conventional MMV problem, and furthermore, if $G = 1$, it reduces to the SMV problem. Therefore, our formulated problem can be regarded as a generalized MMV (GMMV) problem.

B. Performance Gain From SM Signal Interleaving

We discuss the performance gain from the SM signal interleaving by comparing the detection probability of the proposed SSP algorithm with and without SM signal interleaving. Here, we consider a simplified scenario with $N_a = 1$ and uncorrelated Rayleigh-fading MIMO channels. Let m be the index of the active antenna, and for any given l, $\mathbf{H'}_l^{(t)}$'s for $1 \leq t \leq G$ are mutually independent, where $1 \leq m, l \leq N_t$. Based on these assumptions, the received signal is given by $\mathbf{y}^{(t)} = \alpha^{(t)}\mathbf{H'}_m^{(t)} + \mathbf{w}^{(t)}$, for $1 \leq t \leq G$, where $\alpha^{(t)} \in \mathbb{B}$ denotes the signal constellation symbol carried by the active antenna in the tth time slot. To identify the active antenna, the proposed SSP algorithm relies on the correlation operation in *Line 5* of **Algorithm 1**, i.e.,

$$C_l \triangleq \sum_{t=1}^{G} \left| \left(\mathbf{y}^{(t)}\right)^* \mathbf{H'}_l^{(t)} \right|^2 = \sum_{t=1}^{G} \left| \left(\alpha^{(t)}\mathbf{H'}_m^{(t)} + \mathbf{w}^{(t)}\right)^* \mathbf{H'}_l^{(t)} \right|^2$$
$$= \sum_{t=1}^{G} \left| F_{m,l}^{(t)} \right|^2 \tag{5}$$

where $F_{m,l}^{(t)} = (\alpha^{(t)}\mathbf{H'}_m^{(t)} + \mathbf{w}^{(t)})^*\mathbf{H'}_l^{(t)}$ for $1 \leq l \leq N_t$. Due to large N_r in practice, we have $\mathrm{Re}\{F_{m,m}^{(t)}\} \sim \mathcal{N}(\mu_1, \sigma_1^2)$ with $\mu_1 = 0$, $\sigma_1^2 = ((N_r^2 + N_r)\sigma_s^2/(2 - \delta(M = 2)) + (N_r\sigma_w^2/2)$, and $\mathrm{Im}\{F_{m,m}^{(t)}\} \sim \mathcal{N}(\mu_2, \sigma_2^2)$ with $\mu_2 = 0$, $\sigma_2^2 = ((1 - \delta(M = 2))(N_r^2 + N_r)\sigma_s^2/2) + (N_r\sigma_w^2/2)$ according to central limit theorem [14]. Similarly, both $\mathrm{Re}\{F_{m,l}^{(t)}\}$ and $\mathrm{Im}\{F_{m,l}^{(t)}\}$ follow the distribution $\mathcal{N}(\mu_3, \sigma_3^2)$ with $l \neq m$, $\mu_3 = 0$, and $\sigma_3^2 = (N_r\sigma_s^2/2) + (N_r\sigma_w^2/2)$. Note that $\sigma_s^2 = \mathrm{Tr}\{E\{\mathbf{x}^{(t)}(\mathbf{x}^{(t)})^T\}\}$, and $\mathrm{Re}\{F_{m,l}^{(t)}\}$ and $\mathrm{Im}\{F_{m,l}^{(t)}\}$ $\forall\, l$ are mutually independent. Moreover, we can have $C_m \sim \sigma_2^2\chi_G^2 + \sigma_1^2\chi_G^2$ and $C_l \sim \sigma_3^2\chi_{2G}^2$ with $l \neq m$, where χ_n^2 is the central chi-squared distribution with the degrees of freedom n [14]. Since Algorithm 1 only has one iteration and $|\Gamma| = |\Xi| = 2$ in the iteration for $N_a = 1$, we consider $P_{\mathrm{GMMV}}(C_m - C_l^{[2]} > 0 | l \neq m)$ as the correct active antenna detection probability, where $C_l^{[1]} > C_l^{[2]} > \cdots > C_l^{[N_t - N_a]}$ with $l \neq m$ are sequential statistics. The probability density functions (pdfs) of C_m and C_l with $l \neq m$ are denoted by $f_1(x)$ and $f_2(x)$, respectively. The pdf of $C_l^{[2]}$ with $l \neq m$ is $f_2^{[2]}(x) = (N_t - N_a)!/(N_t - N_a - 2)!)(F_2(x))^{N_t - N_a - 2}\,(1 - F_2(x))f_2(x)$, where $F_2(x)$ is the cumulative density function of $f_2(x)$. In this way, we have

$$P_{\mathrm{GMMV}}\left(C_m - C_l^{[2]} > 0 | l \neq m\right)$$
$$= \int_0^{\infty}\int_{-\infty}^{\infty} f(x) f_2^{[2]}(x - z)\, dx\, dz. \tag{6}$$

For the conventional MMV problem with identical channel matrices, similar to the previous analysis, we have $C_m \sim G\sigma_2^2\chi_1^2 + G\sigma_1^2\chi_1^2$ and $C_l \sim G\sigma_3^2\chi_2^2$ with $l \neq m$. Similarly, we can also get $P_{\mathrm{MMV}}(C_m - C_l^{[2]} > 0 | l \neq m)$.

To intuitively compare the signal detection probability, we compare $P_{\mathrm{MMV}}(C_m - C_l > 0 | l \neq m)$ and $P_{\mathrm{GMMV}}(C_m - C_l > 0 | l \neq m)$ when $\sigma_s^2/\sigma_w^2 \to \infty$ and G are sufficient large. In this case, $C_m - C_l$ can be approximated to the Gaussian distribution $\mathcal{N}(\mu_4, \sigma_4^2)$ with $\mu_4 = G(\mu_1^2 + \mu_2^2 - 2\mu_3^2 + \sigma_1^2 + \sigma_2^2 - 2\sigma_3^2)$, $\sigma_4^2 = G\sum_{i=1}^{3} 2\sigma_i^4 + 4\mu_i^2\sigma_i^2$. In this way, we can obtain that $P_{\mathrm{GMMV}}(C_m - C_l > 0 | l \neq m) \approx Q(-\mu_4/\sigma_4)$, where Q-function is the tail probability of the standard normal distribution [14]. By contrast, for the conventional MMV case, we can obtain that $P_{\mathrm{MMV}}(C_m - C_l > 0 | l \neq m) \approx Q(-\mu_4/(\sqrt{G}\sigma_4))$. Clearly, P_{MMV} is larger than P_{GMMV} due to $\mu_4 > 0$ and $G > 1$, which implies that an appropriate SM signal interleaving will lead to the improved signal detection performance.

To achieve the goal that $\mathbf{H'}_l^{(t)}$'s $\forall\, l$, are mutually independent, we consider the pseudorandom permutation matrix $\mathbf{\Pi}^{(t)}$.

In Section V, simulation results confirm the good channel diversity gain from interleaving, whose performance gain approaches that of the case of mutually independent channel matrices in the same group.

C. Computational Complexity

The optimal ML signal detector has the complexity of $\mathcal{O}(M^{N_a} 2^{\lfloor \log_2 \binom{N_t}{N_a} \rfloor})$, which is high for large N_a, N_t, and/or M. The conventional signal detectors [1], [7], [12] have the complexity of $\mathcal{O}(N_t^3)$, which is still high in massive SM-MIMO systems with large N_t. By contrast, for the proposed signal detector, the main computational burden comes from the step of least squares with the complexity of $\mathcal{O}(G(2N_rN_a^2 + N_a^3))$ [8], or equivalently $\mathcal{O}(2N_rN_a^2 + N_a^3)$ per SM signal in each time slot. This indicates that the proposed SCS-based signal detector enjoys the same order of complexity with the CS-based signal detector [11].

V. Simulation Results

A simulation study was carried out to compare the performance of the proposed SCS-based signal detector with that of the conventional LMMSE-based signal detector [1] and the CS-based signal detector [12]. The performance of the optimal ML detector [6] is also provided as the benchmark for comparison.

Fig. 3 compares the simulated and analytical spatial constellation symbol error rate (SCSER) of the SCS-based signal detector in different cases over uncorrelated Rayleigh-fading MIMO channels, where $N_t = 64$, $N_r = 16$, $N_a = 1$, and 8-phase-shift keying (PSK) are considered. For the GMMV case, "i.i.d." denotes the case that $\mathbf{H'}^{(t)} = \mathbf{H}^{(t)}\ \ \forall\, t$ and $\mathbf{H}^{(t)}$'s are independently generated, whereas "interleaving" denotes the case that $\mathbf{H}^{(1)} = \mathbf{H}^{(2)} = \cdots = \mathbf{H}^{(G)}$ and $\mathbf{H'}^{(t)} = \mathbf{H}^{(t)}\mathbf{\Pi}^{(t)}$ with different permutation matrices $\mathbf{\Pi}^{(t)}$'s. Clearly, the analytical SCSER derived in Section IV-B have the good tightness with the simulation results. In addition, the proposed SCS-based signal

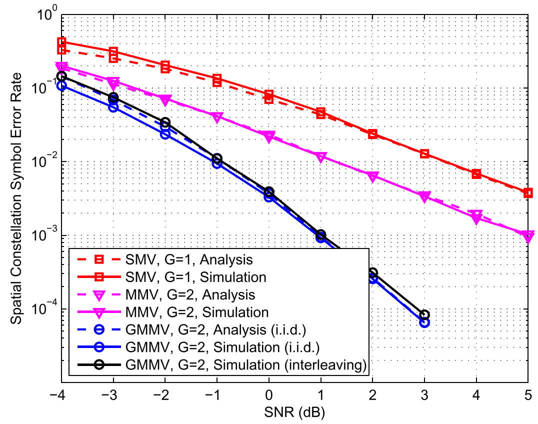

Fig. 3. Comparison of the simulated and analytical SCSER of the SCS-based signal detector in different cases over uncorrelated Rayleigh-fading MIMO channels, where $N_t = 64$, $N_r = 16$, $N_a = 1$, and 8-PSK are considered.

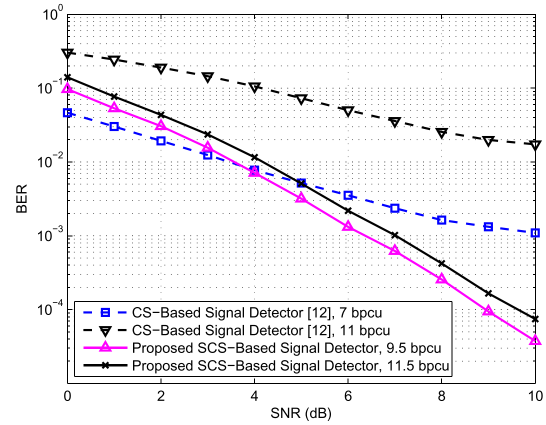

Fig. 5. BER comparison between the traditional CS-based signal detector and the proposed SCS-based signal detector over correlated Rayleigh-fading MIMO channels, where $r_t = r_r = 0.4$ and $N_r = 16$ are considered.

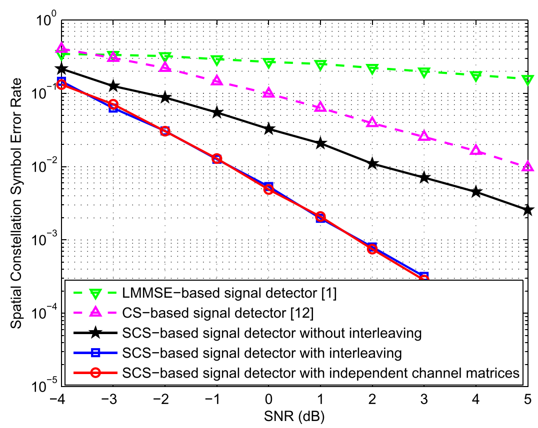

Fig. 4. SCSER of different signal detectors over correlated Rayleigh-fading MIMO channels, where $r_t = r_r = 0.4$, $N_t = 64$, $N_r = 16$, $N_a = 1$, and 8-PSK are considered.

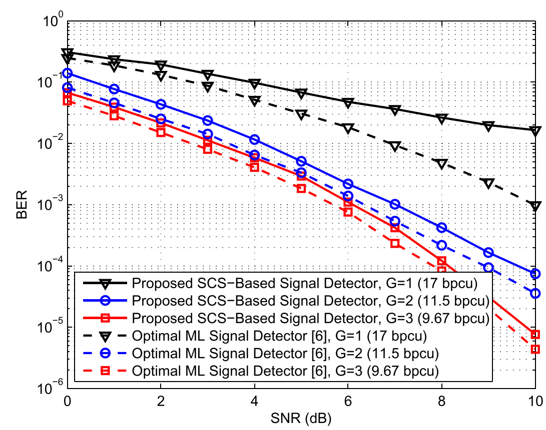

Fig. 6. BER performance comparison between the proposed SCS-based signal detector and the optimal ML signal detector, where $r_t = r_r = 0.4$, $N_t = 65$, $N_r = 16$, $N_a = 2$, and 8-PSK are considered.

detector outperforms the conventional CS-based signal detector since the structured sparsity of multiple sparse SM signals is exploited. Moreover, since the channel diversity can be also exploited, the SCS-based signal detector with mutually independent channel matrices is superior to that with identical channel matrices by more than 4 dB if the SCSER of 10^{-3} is considered. Finally, the performance of the SCS-based signal detector with SM signal interleaving approaches that with mutually independent channel matrices, which indicates that the proposed SM signal interleaving can fully exploit the channel diversity.

Fig. 4 provides SCSER comparison of different signal detectors over correlated Rayleigh-fading MIMO channels, where both the channel correlation coefficients at the transmitter and receiver are $r_t = r_r = 0.4$ [13], $N_t = 64$, $N_r = 16$, $N_a = 1$, and 8-PSK are considered. The conventional LMMSE-based signal detector works poorly due to $N_r \ll N_t$. The SCS-based signal detector with interleaving outperforms the conventional CS-based signal detector and SCS-based signal detector without interleaving. Moreover, it has the similar performance with that with mutually independent channel matrices (i.e., $\mathbf{H}'^{(t)} = \mathbf{H}^{(t)} \quad \forall t$ and $\mathbf{H}^{(t)}$'s are independently generated), which indicates the good channel diversity gain from interleaving, even in correlated MIMO channels.

Fig. 5 provides the BER performance comparison of the existing CS-based signal detector and the proposed SCS-based signal detector with interleaving over correlated Rayleigh-fading MIMO channels with $r_t = r_r = 0.4$ and $N_r = 16$. The existing scheme adopts two transmission modes: 1) $N_t = 64$, $N_a = 1$, and binary PSK with 7 bpcu; and 2) $N_t = 65$, $N_a = 2$, and no signal constellation symbol with 11 bpcu. In contrast, the SCS-based signal detector with $N_t = 65$, $N_a = 2$, and $G = 2$ adopts quadrature PSK and 8-PSK, respectively, and the corresponding data rates are 9.5 and 11.5 bpcu. In Fig. 5, it can be observed that the proposed SCS-based signal detector with even higher bpcu achieves better BER performance than the conventional CS-based signal detector.

Fig. 6 compares the performance of the proposed SCS-based signal detector with interleaving and the optimal ML signal detector, where $r_t = r_r = 0.4$, $N_t = 65$, $N_r = 16$, $N_a = 2$, and 8-PSK are considered. We find that with the increasing G, the BER performance gap between the SCS-based signal detector and the optimal ML signal detector becomes smaller. When $G \geq 2$, the SCS-based signal detector approaches the optimal ML signal detector with a small performance loss. For example, if the BER of 10^{-4} is considered, the performance gap between the SCS-based signal detector with $G = 3$ and the optimal ML detector is less than 0.2 dB. Thus, the near-optimal performance of the proposed SCS-based signal detector can be verified.

VI. Conclusion

This paper has proposed a near-optimal SCS-based signal detector with low complexity for the massive SM-MIMO. First, the grouped transmission scheme can introduce the desired structured sparsity of multiple SM signals in the same transmission group for improved signal detection performance. Second, the SSP algorithm can jointly detect multiple SM signals with low complexity. Third, by using SM signal interleaving, we can fully exploit the channel diversity to further improve the signal detection performance, and the gain from SM signal interleaving can approach that of the ideal case of mutually independent channel matrices in the same transmission group. Moreover, we have quantified the gain from SM signal interleaving. Simulation results have confirmed the near-optimal performance of the proposed scheme.

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Performance Analysis of Neighbor Discovery Process in Bluetooth Low-Energy Networks

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***Abstract*—To support various Internet of Things (IoT) applications, the Bluetooth Low Energy (BLE) standard specifies a wide range of parameter values for the neighbor discovery process (NDP). The parameter values used during neighbor discovery directly affect the performance of the NDP. Therefore, an optimal parameter setting is essential to achieve the best tradeoff between discovery latency and energy consumption. An analytical model can offer a beneficial guideline for such a parameter selection. In this paper, we propose a general model for analyzing the performance of NDP in BLE networks. In the model, the operations of the scanner and the advertiser, which are two main components of NDP, are expressed on the discrete-time axis. Based on the Chinese Remainder Theorem (CRT), the discovery latency and energy consumption of advertiser are derived. The numerical results from our model are almost the same as the simulation results, for any parameter values specified by the standard. When considering that BLE is one of candidate communication technologies for IoT, the proposed model is expected to be very useful in setting the default or initial values of NDP parameters for various IoT applications.**

***Index Terms*—Bluetooth Low Energy (BLE), discovery latency, energy consumption, Internet of Things (IoT), neighbor discovery.**

I. Introduction

Bluetooth low energy (BLE), which is a complementary technology of classic Bluetooth and is targeting ultra-low-power and low-cost communication, has attracted much attention recently as one of the key enabling technologies for the Internet of Things (IoT) [1].

To design an ultra-low-power BLE system, some major modifications were made to the classic Bluetooth, one of which was for the neighbor discovery process (NDP) [2]. All communications in BLE networks must involve NDP in the first place since it enables a BLE device to set up a connection or exchange information with its neighbors. Therefore, it is very desirable to have a fast and energy-efficient NDP. To this end, unlike classic Bluetooth which may use all the available channels for discovery purposes, BLE dedicates only three special channels called advertising channels to neighbor discovery. Note that fewer advertising channels lead to fast discovery and this can give the devices more chances to put their transmitter/receiver electronics into sleep. In addition, BLE adopts more relaxed timing for NDP so that a device can flexibly control its duty cycle during NDP. The timing is determined by several discovery parameters of which values directly affect the NDP performance. The BLE standard specifies a wide range of feasible parameter values for NDP, to support

Manuscript received February 1, 2015; revised August 2, 2015 and December 11, 2015; accepted April 13, 2016. Date of publication April 25, 2016; date of current version February 10, 2017. This work was supported by the National Research Foundation of Korea funded by the Korean Government (MSIP) under Grant 2015R1A5A7037372. The review of this paper was coordinated by Dr. M. Dianata.

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Digital Object Identifier 10.1109/TVT.2016.2558194